Applications of wavelet transform in remote sensing data processing

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ABSTRACT: This communication intends to briefly present the wavelet transform and to demonstrate through a few examples its potential applications in remote sensing. The objects observed in the remote sensing images exhibit many imbricated characteristic scales since our environment is composed of many natural and unnatural processes and hence displays marked heterogeneities. The potentialities and perspectives of this transform to the analysis and processing of remote sensing images are presented.

1 INTRODUCTION

The wavelet theory is the accomplishment of numerous techniques which has been developped only recently for various signal processing applications. After some pionneering works made since the beginning of the century, the first wavelet was used for the analysis of seismic data in the purpose of oil exploration (Grossmann, Morlet 1984). This was the start of a lot of works that bring through an unified theory (Meyer 1990). Wavelet theory treats both the continuous and discrete cases and can be applied to many tasks in signal and image processing where it has numerous potential applications. In particular, the wavelet transform is adapted to the analysis of non-stationary signals of finite energy for which the classical formalism based on variance and correlation function does not hold. Remote sensing images are such a signal. The wavelet transform leads naturally to the concept of multi-resolution analysis (Meyer *et al.* 1987; Mallat 1989; Meyer 1990) which derives from the idea of the Laplacian pyramid introduced by Burt, Adelson (1983).

2 THE WAVELET TRANSFORM

More or less as in the Fourier transform, for which any periodic function is represented as a summation of sinusoids, the wavelet transform makes any arbitrary function as a summation of elementary functions: the wavelets. The respective weights of the wavelets in the summation are called the wavelet coefficients. Besides the fact that periodicity is required for Fourier analysis, the main difference is that wavelets are well-located in both domains: space and scale (Meyer *et al.* 1987; Daubechies 1990; Rioul, Vetterli 1991) while Fourier transform only provides informations on scales for the whole image. Wavelets are functions obtained from a single function, the *mother* wavelet, by dilatations and shifts. At first continuous wavelets were studied but many recent works deal with the discrete wavelet transform (Daubechies 1988; Mallat 1989; Meyer 1990). Some wavelets families were defined: non-orthogonal (Grossmann, Morlet 1984; Daubechies *et al.* 1986), orthogonal or orthonormal (Daubechies 1988; Feauveau 1990; Daubechies 1990; Meyer 1990), bi-orthogonal (Cohen *et al.* 1990; Vetterli, Herley 1990). These families have differents properties and lead to different decompositions (Meyer *et al.* 1987). The orthonormal wavelets ensure the decorrelation of the wavelet coefficients between two different scales.

Wavelet coefficients are a measure of the intensity of the local variations of the signal for the scale under concern. The value of a coefficient will be large when the dilatation of the mother wavelet is close to the scale of the heterogeneity causing the signal to be irregular. On the contrary the coefficients are negligible when the local signal is regular (smooth) for this particular scale. Hence the value of a coefficient for a particular location and at any scale can be understood as a characterization of the structures having this scale and present at this geographical location. The wavelet transform therefore provides a very valuable information about the properties of the analysed image both in space and scales.

3.MULTIRESOLUTION ANALYSIS

Mallat (1989) introduces the concept of multiresolution analysis which considers any function as a limit of successive approximations. The

Table 1: Scheme of a hierarchical pyramid produced by a multi-resolution analysis. See text for more explanations.

<table>
<tr><td>Context image (all scales greater than (j+1))</td><td>Image of the "horizontal" structures at scale (j+1)</td><td rowspan="2">Image of the "horizontal" structures at scale j</td></tr>
<tr><td>Image of the "vertical" structures at scale (j+1)</td><td>Image of the "diagonal" structures at scale (j+1)</td></tr>
<tr><td colspan="2">Image of the "vertical" structures at scale j</td><td>Image of the "diagonal" structures at scale j</td></tr>
</table>

size of the pixel (the spatial resolution of the sensor) defines a reference resolution, or a reference scale of observation, for measuring the local variations within the image. The multiresolution analysis provides a decomposition of the original image in terms of structures or scales which are composing the image. In this purpose, the information content of the image is reorganized in order to exhibit the structures at different resolutions. Mathematically, the structures (also called details in image processing langage) of an image at the resolution j are defined as the difference between its approximation at the resolution j and its approximation at the resolution (j-1). Differently said, in the detail image at resolution j appear all the structures having a characteristical length equal to j, or more exactly comprised between (j-1) and j. This characteristical length can be for example the distance separating two dunes in desert, the typical size of cultures or the wavelength of ocean waves. This image of structures is composed by the wavelet coefficients which are a measure of the intensity of the variation of the signal at this scale j. The greater the absolute value of the coefficient, the greater the intensity of the variation. As an example, let us assume a steep element of topography or a thermal front in the ocean having a width of j. Since the signal is highly variable on this element for each scale less than j, the absolute values of the wavelet coefficients for the relevant pixels will be large, increasing with the scale and peaking for j, while for smooth parts of the image, the wavelet coefficients will be very low. Thus a multiresolution analysis provides a hierarchical pyramid for interpreting the image information in terms of structures (Table 1). In the course of the analysis, the image containing the informations due to the structures which scales are greater than the current scale is called "context image". If the analysis is pursued, this context image will be in turn decomposed in details and another context image.

An example of multiresolution analysis by wavelet transform is now provided. This example deals with a SPOT image of the ocean, of the eastern coast of India, close to Madras. This image has been selected because it clearly exhibits structures having different characteristic scales (Rivereau 1990). The near infrared channel (XS3) is presented in Fig. 1a. Mostly two differents kinds of structures appear. The most pronounced ones are quasi-vertical and are due to a swell of a few hundred meters in wavelength modulated by an internal wave. The interface between the upper water layer and the middle one of higher density is called the pycnocline and is located at say one hundred meters depth. It is often the seat of oscillations which give rise to small oscillations of the elevation of the sea surface. Swell also modifies the sea surface. These oscillations locally change the mean slope of the wavelets reflecting the solar light, making the swell and the internal wave clearly visible in this image. The wavelength of the swell is proportional to the square root of the depth. As the swell propagates westwards (towards the left of the image), it encounters decreasing depths as it approaches the continental shelf. Therefore the wavelength decreases and so does the distance between the vertical crests seen in the image from the right to the left. Superimposed to this swell are the wind waves which exhibit shorter wavelengths of a few tens of meters. Its propagation axis is oriented NW-SE. Fig. 1b displays the multiresolution analysis of this image at scales 20 and 40 m. Because the wavelength of the wind waves is smaller than 80 m, they do not appear in the context image which contains only structures of characteristic scales equal or greater to 80 m, such as the swell which is clearly visible. The horizontal details image at 20-40 m

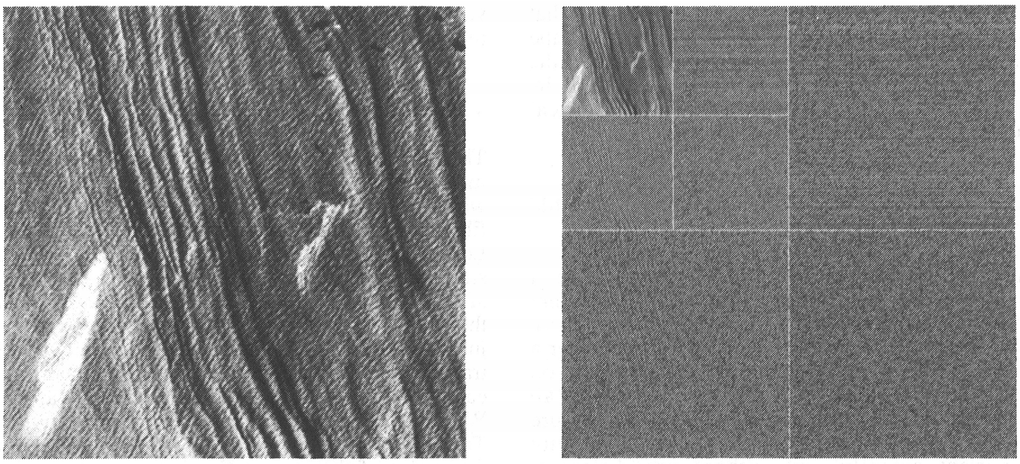

Figure 1: Multiresolution analysis of a SPOT image of the ocean. (a) Original image of the XS3 channel (near infrared). Resolution is 20 m. Sizes of image are 512x512. (b) decomposition into context image (resolution 80 m) and details images (characteristics lengths comprised betwenn 20 and 40 m, and 40 and 80m) according to the scheme of Table 1.

exhibits the structure of the noise affecting the sensor. This noise is also present at 40-80 m. The vertical details images at 20-40 and 40-80 m displays the small-scale structures carried by the crests of the swell, making them visible. The wind waves structures affects all the details images (20-40, 40-80 m) and are better seen for the diagonal direction, though hardly visible in the picture. For this example of a 512x512 image, the computation time for the entire analysis was about 1 minute. An Unix 20 Mips workstation was used.

4 CONCLUSIONS AND PERSPECTIVES

The wavelet transform is a very new mathematical tool and many efforts must still be devoted for a full understanding of its properties. A number of studies applying wavelet transform to remote sensing images are underway, at least in France and particularly in various institutes in Nice - Sophia Antipolis. The domain of applications is rather wide and some of them will be discussed. Among the most promising are the followings.

4.1.Analysis of the spatial structures present within an image

The wavelet transform leads to a scale-decomposition of the spatial structures observed within an image. Hence it provides an efficient characterization of these structures, the knowledge of them being important in many fields of Earth sciences. More readable results are expected from the wavelet transform compared to the current use of structure functions or variograms in the analyses of images in terms of structures and characteristic scales (Deschamps *et al.* 1981; Crépon *et al.* 1983; Carr, Myers 1984; Wald 1985; Gilli 1985; Curran 1988; Besnus *et al.* 1990). Also one should underline the less computer-time required by the wavelet transform. The analysis of the evolution in time of spatial structures is similar in essence and can benefit from the wavelet transform (Proenca, Flouzat 1990).

4.2.Merging images with different spatial resolutions and fusion of data

The complexity of the natural processes requires for their study a large amount of data and particularly of remote sensing data. For this purpose, it is necessary to be able to merge images taken at different spatial resolutions, which implies at least their geometrically superimposition. Using the wavelet transform, it is possible to obtain representations of all the images at the lowest resolution found in the data set, *i.e.* at the greatest pixel size, and to merge them by the means of current methods making use of template matching and maximum cross-correlation techniques. Then the merging model is applied to all the scales, from the largest down to the lowest. An important effort has been made in this field by the research team of Roger Manière at University of Nice, France. The resulting methods permit to geometrically merge images originating from different sensors: Landsat-TM and -MSS, NOAA-AVHRR (paper in preparation). It should be pointed out that in any case, the use of structures matching in data merging implies that there exist sufficiently numerous structures homogeneously distributed within the scene, in order to define an accurate geometrical model, and that these structures are conservative features with the wavelength, *i.e.* that they are observed at any of the involved wavelengths. Such an approach and its restrictions are also valid for the geometrical superimposition of time-series of images.

4.3.Segmentation and classification of multi-spectral images

Many of the recent methods for the classification of multi-spectral images make use of a few texture informations found within each spectral image. These informations as well as the spectral values enter a classification scheme, including recent works on neural networks, which produce a synthesis of all these data. The exact definitions of the texture parameters used in such an approach are not important actually and authors use differents quantities to describe the texture, *i.e.* the local variation of the signal: variance, contrast, maximum difference, entropy, gradient, or even structure functions (Chen *et al.* 1989; Kaifel, Loeher 1992; Key 1990; Kuo *et al.* 1989; Welch *et al.* 1988a, b, c, 1989). Since the wavelet transform provides a complete description of the texture of the image at all available scales, it is expected that sound results can be reached by using wavelet coefficients in classification schemes, although no direct relationship can be found between these coefficients and the few texture parameters currently used. It permits to make fully use of the spatial information and at least to discriminate regions which do not present similar large scales.

4.4.Change of the information content with the resolution

Since classifiers are currently using spatial statistics, it is important to study how these statistics behave with changing sensor resolution if images taken by various sensors are to be used in a study. A similar problem arises if one wants to use both high and low-resolution sensors to monitor an environmental parameter such as the normalized difference vegetation index (NDVI) or the temperature. A very few works have dealt with the change of information content with resolution. Woodcock, Strahler (1987), Kong (1987), Kong, Vidal-Madjar (1988), Townshend, Justice (1988) demonstrate that the local variance of land scenes strongly depends upon the relationship between the size of the objects in the scene and the resolution. It has been shown that a scene-dependent threshold exists in resolution below which the pertinent statistical information disappears. Similar works have been accomplished for clouds scenes and are for example cited in Welch *et al.* (1989). The multiresolution analysis by the means of wavelet transform is an efficient approach for such studies. It has also an impact on the merging of data from different sensors since it can be provide the range of scales at which informations from the various sensors are similar and indicate the benefit of merging.

4.5.Speckle removal in SAR imagery

The SAR imagery is affected by the presence of a multiplicative noise, called the speckle. One current way to suppress it consists in applying an adaptative filter to the Fourier coefficients of the image (see *e.g.* Lopes *et al.* 1990). This implies a filtering of all the structures within the image while they may not be affected the same way by this noise. To overcome this drawback, it is proposed to decompose the image into its various scales by the means of the wavelet transform, then to apply the Fourier transform to each set of wavelet coefficients and to apply a Wiener's filter to each set of Fourier coefficients. Then, the wavelet coefficients are reconstructed by the means of the inverse Fourier transform and the synthesis of these filtered wavelet coefficients gives an image with the speckle filtered out. Preliminary results are very encouraging and show that the latter filtering method results into sharper structures that the former.

4.6.Data compression

Remote sensing systems are producing huge amounts of data and space agencies as well as users are since long aware of the problems that are posing by the handling and the archiving of such data. Data compression may help reducing the volume of data and wavelet transform is one of the many tools that are used to compress data (see e.g. Antonini *et al.* 1990; Antonini 1991). Applying wavelet transform permits to decorrelate the data and thus to reduce the redundancy of the data, allowing for a compression without any loss of information. If degradation of information is accepted for a greater compression rate, it can be done at selected scales according to the needs.

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